Style Based Robotic Motion

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***Abstract*— In this paper, we present an approach to motion sequencing and generation in which "style of motion" is taken into account in a systematic manner. In particular, we present a method for injecting so-called dynamic efforts into a discrete motion sequencing framework that utilizes existing theory of stylistic human movement to inform a principled approach to generating trajectories. Namely, choosing weights in a linear-quadratic cost function leads to trajectories corresponding to the eight basic effort qualities found in dance theory; each weight scales a different *motion factor* that describes an element of style perceived by an audience. Combined with a style-sensitive motion sequencing scheme, we can fully describe stylistic system behavior. Thus, this paper also reports on the application of this general framework to the problem of generating motion sequences for a humanoid robot that exhibit distinctly different stylistic behaviors though they are composed from the same underlying building blocks.**

I. Introduction

Style is a subjective impression of movement – a quantity largely perceived by the viewer that is hard to quantify with traditional engineering tools. The academic areas of planning and control produce movements that may also be perceived as being in a certain style: one in selecting and sequencing movements, the other in generating the exact trajectory of each movement. Typically the parameters established in both these realms deal with task dependent quantities like achieving a spatial goal and moving with minimum energy, respectively. However, in some applications, we may require parameters which offer control over the sequence and expression of actions that are sensitive to how these motions are *perceived* by a viewer. That is, we'd like to control the *style* of motion.

As such, we turn our attention to the group of people who make their living by producing stylistic motion, giving particular attention to the effect on their audience – dancers. Academics and theoreticians in the field of dance typically have one of two broad foci: either they study the effect of a choreographer's work, its place in history and culture, and the novel mechanisms for composition employed by the artist; or they examine the mechanics and psychology of human movement, producing effective training programs and exercises that allow dancers to exhibit a greater control over a greater range of motions and motion qualities. It is the latter focus, where one of the most notable scholars is Rudolf Laban, that is of interest in this paper. Laban is perhaps most famous for his dance notation system which is built upon his principles of the body's geometry and movement's dynamic quality[1]. Here we draw direct inspiration from his work in movement quality: his system of movement *efforts*. [9], [16]

When dancers learn a piece, they first learn the order of the various steps the choreographer has arranged. Then, they spend many rehearsals refining the dynamic qualities which they impart to these sequences of steps, and it is this aspect of dance practice that Laban's effort system aims to better facilitate. Moreover, this process inspires the stance we will take in this paper: we sequence movements in a given style and subsequently scale these motions with the appropriate dynamic quality.

Such a stance inherits some concepts from the body of work that has attempted to segment dynamic motion primitives (*movemes* [5]) which may be combined to create full-fledged movement sequences [7], [6], [4]. However, here, we take a generative approach to producing such building blocks that is rooted in Laban's theory. As such our blocks have parameters that correspond to the aspects of movement which an audience notices. Previous work (i.e. [4], [15], [10], [14]), which aim to elucidate an understanding of style, typically learn statistical models from real data. In this paper we complement this work with a method rooted in dance theory with the hopes of producing a more corporally meaningful and viewer sensitive template for such statistical extractions. Previous attempts at "stylizing" robotic motion [8], which have aimed to facilitate better human-robot interaction, have not focused on this shift in point-of-view.

We divide our problem of enumerating stylistic parameters into two parts, sequencing and control. On the side of control, we formulate a linear-quadratic optimal control problem that generates an optimal trajectory as described by weights which correspond with Laban's *motion factors*. Then, employing our framework in [12], we present both installments, "sequencing" and "control," implemented in simulation and on a humanoid robot where instances of parameters from both halves describe a *stylistic task*.

Thus, the first contribution of this paper, presented in Sec. II, is a mapping between Laban's theory of movement effort and parameters which have meaning in a control theoretic setting. In Sec. III we use this mapping as a method for imparting dynamic quality to a sequence of movements. We then present two instantiations of stylized robotic motion on the Aldebaran NAO robotic platform to show the effectiveness of two inherently different robotic behaviors when implemented using this framework. Tweaking the underlying movement structure (an automaton assembled

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[1]These have some analog with the notions of kinematics and dynamics in engineering, respectively.

as in [12] whose transitions enumerate allowable stylistic sequences) and changing the weights used to generate the timed transition, we produce radically different movement sequences. Section IV delves more deeply into our philosophical motivation and what kinds of tools can augment the basic principles presented here.

II. From Laban to Optimal Control

Here we present a linear quadratic optimal control framework that allows us to find time-varying trajectories between static poses. The weights in our cost function correspond to the effort system laid out by Rudolf Laban in the early 20th century. This set of codified terms and concepts continues to influence how dancers describe their movement and how they train themselves to perform a greater range of movements[2]. Namely, this vocabulary entitles dancers to a detailed description of movement that measures dynamic quality thus helping to determine an execution that produces the desired effect on the viewer.

Laban names four categories of effort or *motion factors*: *space*, *weight*, *time*, and *flow*. Space, weight, and time deal with individual movements, interrelated via the structure in Fig. 1, while flow describes the connection among a succession of movements; each are described in detail in [13], [16]. In a given instance of a movement, each factor may take on one of two qualities. These qualities represent the extreme notions of each motion factor, and our framework will generalize this binary scale to one of continuously variable weights.

Three motion factors, space, weight, and time, describe the *effort* an individual movement may posses. Their relationship can be seen in Laban's *dynamosphere* as in Fig. 1. The extremes of these three motion factors combine pairwise to form the eight basic efforts: dabbing, gliding, floating, flicking, thrusting, pressing, wringing, and slashing. Each of these terms corresponds to a familiar pedestrian action, highlighting, even to a lay audience, the nature of the dynamosphere arrangement: changing the quality of one motion factor moves around the cube to a different basic effort. These three motion factors, and the fourth factor, flow, which describes the quality of the connection between movements, are described – along with some intuition behind our mathematical interpretation – in the next four paragraphs; we continue to base our discussion of Laban in [13], [16].

The space axis describes how the dancer's attitude toward space is perceived. *Flexible* movements seem more carefree, meandering, and indirect; *direct* motions appear more matter of fact and judicious with their use of space. We pair this concept with a system's notion of reference tracking; direct movements track their path more aggressively than flexible ones. Thus, we will make use of nominal trajectories away from which our solutions may deviate or adhere closely.

The axis of weight deals with the emanated sense of weight in the dancer's body during the movement. *Light* movements look as though they are less influenced by gravity – perhaps they are effortless – whereas *strong* movements are muscular and seem taxing on the body to perform. We interpret this as a specification for how much control effort is used to perform the movement, or, in terms of a cost function, how "cheap" it is to increase the magnitude of the control signal.

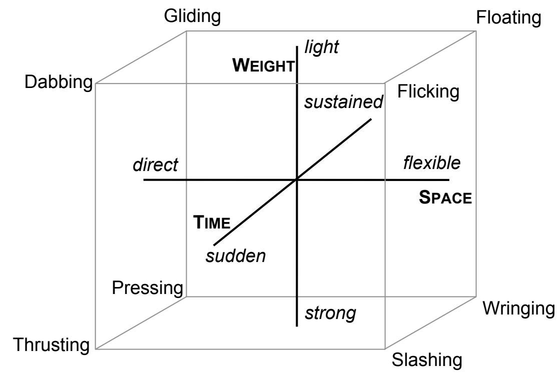

Fig. 1. The dynamosphere. Laban's arrangement of eight basic efforts according to the axes of space, weight, and time. In bold font are the three Laban *motion factors* which deal with single movements; in italics are the two qualities Laban associates with each factor; and in plain font are the eight basic efforts which result from the pairwise combination of each quality. [16]

Thirdly, Laban prescribes a time axis on which the movement may either be *sudden* or *sustained*. This describes a quality which, while it adheres closely to the colloquial notion of these terms, is more subtle than just the duration of the movement; that is, a movement which lasts five seconds may be executed with a sudden or sustained quality. We interpret this as a metric over how much the state of the system is allowed to change: during a sustained movement it should change less while in a sudden movement it may deviate wildly to produce a trajectory that appears to the audience as frantic.

Finally, Laban describes transitions between movements with flow; these may either be *free* or *bound*. In free flow a dancer seems to move through movements confidently with less care for precise execution; while in bound flow, the dancer appears more careful to execute the succession of movements precisely. We interpret this from a systems perspective as a lesser (or greater) desire for the dancer to hit poses between movements exactly. In the sequencing framework we will employ, this translates to varying the weights on a terminal pose.

To make these concepts mathematically rigorous, consider a system with an input $u = [u_1, u_2, ..., u_m]^T$, a state $x = [x_1, x_2, ...x_n]^T$, and an output $y = [y_1, y_2, ...y_l]^T$ which tracks a reference signal $r = [r_1, r_2, ...r_l]^T$. We establish a quadratic cost function

$$J = \frac{1}{2}\int_0^{T_f} \left[(y-r)^T Q(y-r) + u^T R u + \dot{x}^T P \dot{x}\right] dt + \frac{1}{2}(y-r)^T S(y-r)\Big|_{T_f} \quad (1)$$

[2]Today, Laban's direct influence is seen through Certified Laban Movement Analyst (CMA) training programs where Laban's technique and theory are taught.

in order to find an input u principled on the matrices $Q \in \mathbb{R}^{l\times l}$, $R \in \mathbb{R}^{m\times m}$, $P \in \mathbb{R}^{n\times n}$, and $S \in \mathbb{R}^{l\times l}$. By construction, each of these matrices are positive definite and symmetric. Furthermore, their entries create a continuously varying, quantitative version of Laban's effort system and will determine which movement qualities are exhibited by the optimal trajectory, i.e. the output trajectory may be bound, direct, sudden, and strong.

Specifically, we associate the weight Q to the Laban's motion factor space, R with the factor weight, P with time, and S with flow. These weights correlate with the quality of each factor as follows:

$$Q \sim \textit{direct} \tag{2}$$
$$R \sim \textit{light} \tag{3}$$
$$P \sim \textit{sustained} \tag{4}$$
$$S \sim \textit{bound} \tag{5}$$

where the opposite of the qualities listed, flexible, strong, sudden, and free, are respectively achieved when these weights are relatively small.

Using these weights as the style-based parameters for varying the resulting trajectory, we solve the optimal control problem

$$\begin{aligned} &\min_u J \\ &s.t. \\ \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{6}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, and $C \in \mathbb{R}^{l\times n}$.

Differentiating the Hamiltonian

$$H = \frac{1}{2}[(y-r)^T Q(y-r) + u^T Ru + \dot{x}^T P\dot{x}] + \lambda f$$

with respect to u and x gives us a first order necessary condition (FONC) for optimality and the dynamics of our costate $\lambda = [\lambda_1, \lambda_2, ...\lambda_n]$:

$$\begin{aligned} \frac{\partial H}{\partial u} &= u^T(R + B^T PB) + x^T A^T PB + \lambda B = 0 \\ &\Rightarrow u = -(R + B^T PB)^{-1}(B^T PAx - B^T\lambda^T) \end{aligned} \tag{7}$$

$$\begin{aligned} \frac{\partial H}{\partial x} &= -\dot{\lambda} = x^T(C^T QC + A^T PA) + u^T B^T PA \\ &\quad + \lambda A - r^T QC \\ \Rightarrow \dot{\xi} = \dot{\lambda}^T &= (A^T PB(R + B^T PB)^{-1}B^T PA - C^T QC \\ &\quad -A^T PA)x + (A^T PB(R + B^T PB)^{-1}B^T - A^T)\xi \\ &\quad + C^T Qr \end{aligned} \tag{8}$$

Applying the transversality condition we obtain:

$$\xi(T_f) = C^T SCx(T_f) - C^T Sr(T_f). \tag{9}$$

To solve this system for an optimal $x(t)$ we need to find ξ_0 Thus, we assemble a new state $z = [x, \xi]^T$. Now

$$\dot{z} = Mz + Nr \tag{10}$$

where the entries of M and N are determined from Eqs. 6 - 8 and are given below:

$$M_{11} = A - B(R + B^T PB)^{-1}B^T PA \tag{11}$$
$$M_{12} = -B(R + B^T PB)^{-1}B^T \tag{12}$$
$$\begin{aligned} M_{21} = A^T PB(R + B^T PB)^{-1}B^T PA \\ -C^T QC - A^T PA \end{aligned} \tag{13}$$
$$M_{22} = A^T PB(R + B^T PB)^{-1}B^T - A^T \tag{14}$$
$$N_1 = [0]_{n\times l} \tag{15}$$
$$N_2 = C^T Q. \tag{16}$$

We know that in general

$$z(T_f) = e^{MT_f}z_0 + \int_0^{T_f} e^{M(T_f - t)}Nr(t)dt \tag{17}$$

so let

$$z(T_f) = \Phi z_0 + q \tag{18}$$

where

$$\Phi = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix} \tag{19}$$

$$q = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix}. \tag{20}$$

Combining Eq. 9 with Eqs. 18, 19, and 20 we get

$$\begin{aligned} \xi_0 = (C^T SC\Phi_{12} - \Phi_{22})^{-1}[(\Phi_{21} - C^T SC\Phi_{11})x_0 \\ + C^T SCq_1 + q_2 + C^T Sr(T_f)]. \end{aligned} \tag{21}$$

Thus, we have found our initial condition $z_0 = [x_0, \xi_0]^T$. When combined with Eq. 10, this gives the optimal $x(t)$ (and thus $y(t)$) as nominated by the weights in Eq. 1.

III. Motion Sequencing and Control

Now we demonstrate the combined utility of the framework presented in the previous section and the one in [12] for specifying desired stylistic robotic behavior[3]. As an illustrative example, in this section we construct a disco dancing and a cheerleading behavior. We produce pose sequences that are perceived by viewers as being different - although they are actually composed from the same underlying poses - and animate them on the Aldebaran NAO robotic platform. Further, we simulate dynamic trajectories which, by varying weights in a cost function, emote very different attitudes toward movements.

First, we construct two instantiations of one-arm automata $\mathcal{G}^{disco}_{arm_{1,2}}$ and $\mathcal{G}^{cheer}_{arm_{1,2}}$, a continuous feasibility set O^{NAO}_{infeas}, and two corresponding sets of unaesthetic[4] states $X^{disco}_{unaesth}$ and $X^{cheer}_{unaesth}$. These objects are described in more detail below and assemble to create an automata which establishes allowable sequences of movements for both arms as in [12]. Then, we enumerate two sets of weights $\{Q, R, P, S\}_{disco}$

[3] Where we use the term more as biologists [17] than roboticists [2].

[4] Notions of beauty are often turned on their head in the arts. So note that we use the word "aesthetic" as a noun throughout this paper. That is, our framework defines *an* aesthetic within which poses and motions are either appropriate or inappropriate.

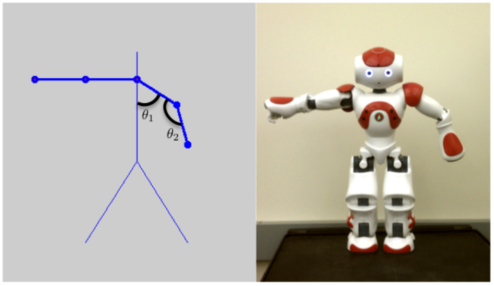

Fig. 2. The discrete states are interpreted as poses corresponding to two joint angles: shoulder and elbow as restricted to the body's coronal plane. On the left is the simulated view of the pose, and on the right is a corresponding pose on the actual robotic platform.

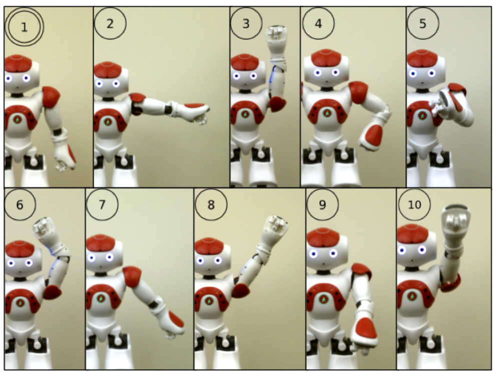

Fig. 3. An illustration of the ten arm poses and their corresponding discrete states which are used throughout this section – namely, in Figs. 4 and 5.

and $\{Q, R, P, S\}_{cheer}$ and a cost function corresponding to the one in Eq. 1, which determine the effort quality of our trajectory. Thus, we specify rules for motion sequencing and the dynamic timing each motion should exhibit for both movement styles.

Each state of the one-armed automata, which corresponds to a single arm pose, is constructed from a pair of joint angles, (θ_1, θ_2), as shown in Fig. 2. These poses were chosen such that the degrees of freedom of the arm (limited to the body's coronal plane) were discretized in a reasonable way and are shown in Fig. 3. Most of the poses have a fully extended elbow except some common examples of when the elbow bends in human behavior, i.e., "hands on hips" and "hands clasped at chest" (poses 4 and 5, respectively). More importantly, we represent shapes critical to the experience of behaviors such as cheerleading and disco-style dancing.

The state transitions (events) correspond to movements, i.e., "put hand on hip" and "extend arm straight out." The fact that a given stylistic task allows certain basic movements and disallows others is accounted for using the presence and absence of state machine transitions, respectively. In particular, X^{disco}_{arm}, E^{disco}_{arm}, f^{disco}_{arm}, and Γ^{disco}_{arm} are defined in Fig. 4. (Note that, for clarity, we neglected to draw the self-loops that are needed at each state to capture the definition of our transition relation in [12].) Moreover, the rest position is given by state 1, and as we always aim at returning to that pose, we let our initial state $x_0 = 1$ and our marked

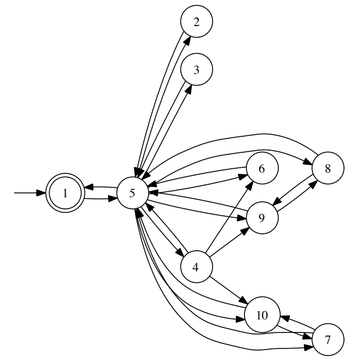

Fig. 4. The discrete event system outlining the one arm motions for the "disco" behavior. States correspond to poses (see Fig. 3) defined by two joint angles: shoulder (as limited to the coronal plane) and elbow. Events are given by primary movements plus the empty event (or hold), which corresponds to undrawn self-loops.

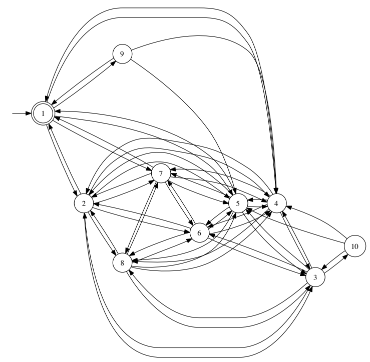

Fig. 5. The discrete event system outlining the one arm motions for the "cheer" behavior.

states $X_m = \{1\}$. The resulting marked language, i.e., the set of event strings that start at x_0 and end in X_m, produce feasible pose sequences recognizable as being in a style of disco dance[5]. Likewise, X^{cheer}_{arm}, E^{cheer}_{arm}, f^{cheer}_{arm}, and Γ^{cheer}_{arm} are defined in Fig. 5. Note that $\mathcal{G}^{disco}_{arm_{1,2}}$ and $\mathcal{G}^{cheer}_{arm_{1,2}}$ have the same initial and marked states.

A left arm and right arm version of each of these one-armed systems are composed with each other producing an automaton describing potential two-armed motion sequences; however this composition will be greedy and allow for physically infeasible and stylistically insensitive sequences. Thus, we further specify a region O^{NAO}_{infeas} which corresponds to infeasible trajectory pairs given our ten states and body geometry. This region is consistent with transitions whose trajectories will intersect, which for this set of states and our platform configuration, is any trajectories which end in

[5]As disco is not as formalized as a genre like classical ballet (which also has many variants), this should be considered our own interpretation of disco dance as applied to this platform. Nevertheless, what we refer to as "disco" in this paper is a distinct style of movement from the style we call "cheer" and from free-form unconstrained movement.

both arms in pose 9 or both arms in pose 10. Here, we omit an explicit definition of $X^{disco}_{unaesth}$ and $X^{cheer}_{unaesth}$, sets of disallowed two-arm states, but for example they both contain the nondescript pose $(5,7)$ while $X^{disco}_{unaesth}$ includes the poses $(1,2)$ and $(2,1)$ - an angular positioning of the arms that is, conversely, allowed in the cheerleading behavior.

Pulling these components together, the final motion sequencing systems which evolve according to the styles of disco and cheerleading on the NAO robotic platform $\mathcal{G}_{disco}$ and $\mathcal{G}_{cheer}$ are given respectively by

$$aesth(infeas(\mathcal{G}^{disco}_{arm_1} \times \mathcal{G}^{disco}_{arm_2}, O^{NAO}_{infeas}), X^{disco}_{unaesth}) \quad (22)$$

and

$$aesth(infeas(\mathcal{G}^{cheer}_{arm_1} \times \mathcal{G}^{cheer}_{arm_2}, O^{NAO}_{infeas}), X^{cheer}_{unaesth}) \quad (23)$$

where the operators $aesth$ and $infeas$ remove physically and stylistically insensitive transitions from the two-armed product automaton as defined in [12].

Finally, the framework presented here is able to scale the timing of these trajectories with the stylistic knobs we outline in Sec. II. Namely, we consider a 4-dimensional system with double integrator dynamics where $x = [\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2]^T$, $u = [u_{\theta_1}, u_{\theta_2}]^T$, and

$$\dot{x} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} u \quad (24)$$

$$y = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x. \quad (25)$$

We then select the following weight matrices for Eq. 1:

$$\begin{cases} Q_{disco} = 0.1 \cdot I \\ R_{disco} = 0.1 \cdot I \\ P_{disco} = I \\ S_{disco} = 100 \cdot I \end{cases} \quad \begin{cases} Q_{cheer} = I \\ R_{cheer} = I \\ P_{cheer} = 10 \cdot I \\ S_{cheer} = 100 \cdot I \end{cases} \quad (26)$$

where I is the identity matrix. The nominal movement reference signal, r, which Eq. 1 encourages the system to track, is simply the linear interpolation between the desired end poses given by the motion sequence.

The relative scaling of these matrices reflects the fact that we'd like the disco behavior to be loose but confident; hence, we employ a small weight on trajectory following (Q_{disco}) and a large one on end point matching (S_{disco}) to produce a trajectory that is, in Laban's terms, flexible and bound. We would also like this behavior to be more energetic. Thus, we employ a small weight on our input (R_{disco}) and change in state (P_{disco}) creating trajectories which are also strong and sudden. On the other hand, the cheer behavior is more rigid but still confident (which implies a larger Q_{cheer} and large S_{cheer}) and energetic but somewhat sustained (larger R_{cheer} and P_{cheer}). Thus, in Laban's framework these trajectories are direct, bound, light, and sustained.

In order to test the effectiveness of our chosen rules and weights (as these behaviors which we define are subjective and require a human eye to validate), we generate random allowable sample paths for both behaviors. The results are animated in simulation and on the Aldebaran NAO humanoid robotic platform; snapshots are provided in Fig. 6.

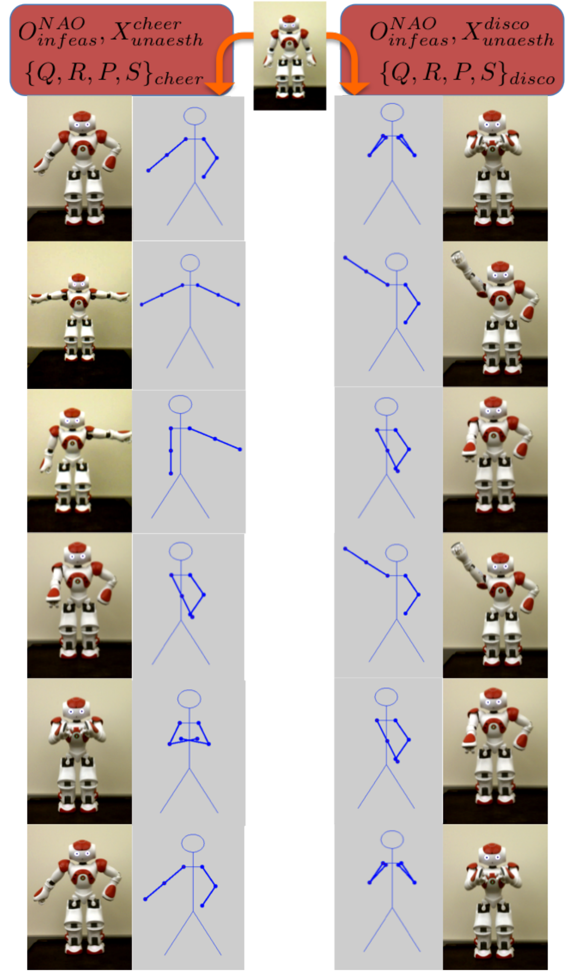

Fig. 6. Two example (partial) sequences demonstrate the result of our control method. The left-hand sequence is an example of the system evolving under the "cheer" constraint while the sequence on the right is illustrating the "disco" style.

Significant changes take place between the distinct cases of systems we animated. Namely, the disco style enforces movements which are largely below the shoulders, as most casual social dancing styles exhibit. The notable exception to this generalization is the distinctive motion when the arm raises up, away from the body, and moves contralaterally and down towards the hips. This classic disco motion recurs frequently when the NAO is moving according to the disco task. Furthermore, the dynamic quality of the simulated movements are loose, imprecise, and give the impression of someone who is carefree and having a good time.

On the other hand, when in the cheerleader mode, the NAO displays not only poses associated with cheerleaders, but also moves frequently through positions with the hands on hips or clasped in front of the chest. In other words, it is not just the shape of the robot that calls to mind a cheerleader association but also the motions the system is performing as it moves between poses. The dynamic quality in this case is more rigid and purposeful; this gives the feeling that the mover is imparting great, specific effort into the movements.

IV. Towards a Method for Robotic Specification

Robotic algorithms often focus on solving concrete tasks, e.g., "go to a specified goal while avoiding obstacles" or, less canonically, "fold this towel." Such tasks imply constraints and objectives that provide the particulars of a movement sequence to accomplish the task. However, less research addresses tasks such as "move according to a specified style," e.g., "do the disco." This paper has addressed motion sequencing and subsequent time-scaling for exactly such a *style*-based task. In particular, we may think of the movement styles exhibited, for example, by classical ballerinas, disco dancers, and cheerleaders as differentiated by distinct stylistic tasks.

Through a study of dance theory we have presented cost function parameters which correspond to aspects of motion which, as they are varied, are perceived by an audience as producing different styles of timing and effort. That is, we have provided a control-theoretic explanation for what dancers understand with kinesthetic intuition. Furthermore, we have instantiated two grammars for motion sequencing and corresponding weights for optimal trajectory selection, implementing disco dancing and cheerleading stylistic tasks. This specification leads to a system which behaves not according to functional objectives but evolves such that stylistic rules are obeyed.

Thus, we have constructed a robotic system – a system which functions automatically based on some internal model of the world – that moves with a given style. On the one hand, this is a little bit mind-blowing because it is entirely unclear as to what otherworldly forces govern the accumulation of stylistic movement rules. Unlike standard control strategies which make use of natural constants like mass and gravitational acceleration, the equations for this natural behavior have no such known constants.

However, this is enabled by the framework we employ that endows robotic systems with consistent behaviors which may or may not have a well understood underlying function. The framework's generality allows us to encode rules which govern stylized, timed motion sequences. Such rules do not have known concrete, functional goals and encoding them may give us future insight into the motivation which produces aesthetic phenomenon.

This type of construction, which employs finite automata and standard techniques from control theory, is easily amenable to incorporating more sophisticated methods for control and movement analysis. For example, temporal logics may be used to encode more complex rules than those used here, as in [11]. On the side of movement analysis, learning techniques (as in [3], [1], [4]), potentially informed by the structure created in our cost function, may be able to construct a one-arm automata automatically, in order to better reflect actual human behaviors. Such extensions could enrich the set of stylized human motions we can capture and also allow for variations in the "personalities" – perhaps based on a given individual's movement style – of these motions.

As we approach a society with greater interface with robotic systems, endowing these systems, particularly humanoid ones, with stylistic capabilities is a field of growing interest. It is well known that body language (as evidenced by public orators in political speeches) and even choreographed movements (as evidenced by dancers in performing arts) are key aspects of human-to-human interaction. Hence, we need to begin developing methods in robotics to tap into this channel of nonverbal communication.

Acknowledgment

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